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Artificial Intelligence based Classifier for Sleep Disorder Detection Using EEG-BCI Data

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ABSTRACT

This paper reports on the development and analysis of machine learning based classifiers for the detection of the sleep disorder, apnea. The Support Vector Machine (SVM) and Random Forest (RF) classifiers are considered as the potential algorithms and training and testing with EEG data is carried-out. Based on the performance analysis, the RF classifier is found to be more suitable for the apnea detection application and hence the FPGA implementation of random forest classifier is done.

Keywords: — Sleep disorder, Apnea, Classifier, Random Forest.

I. INTRODUCTION

A Brain–Computer Interface (BCI), often called a Mind-Machine Interface (MMI), or sometimes called a direct neural interface or a Brain–Machine Interface (BMI), is a direct communication channel between the brain and an external device. Brain-computer interface (BCI) is an upcoming technology which aims to convey people's intentions to the outside world directly from their thoughts, enhancing cognitive capabilities. Mental activity leads to changes of electrophysiological signals like the Electroencephalography (EEG). EEG is a measurement of potentials that reflect the electrical activity of the human brain. It is a readily available test that provides evidence of how the brain functions over time. The EEG is the often used tool by the scientists to study brain functions and it is also an important tool for the physicians to diagnose neurological disorders. The study of the brain electrical activity, through the EEG records, is one of the most important tools for the diagnoses of neurological diseases, such as epilepsy, brain tumor, head injury, sleep disorder, dementia and monitoring depth of anesthesia during surgery etc.

There are several sleep disorders which have different levels of severity and can have an adverse effect on the physical and emotional wellbeing of humans. The most common one is termed as Sleep Apnea (SA). SA refers to the intermittent breathing or gaps in breathing during sleep. It also includes low breathing activity. This condition of breathing with intermediate pauses is known as an apnea, and it can vary widely in frequency and duration [1]. In some instances apnea can lead to critical ailments like heart stroke and early diagnosis and proper treatment cannot save lives. In spite of its importance, most of the cases stay undiagnosed mainly due to the inconvenience and availability issues related to traditional testing methods. Several studies had been conducted to achieve early detection of diseases using artificial intelligence and machine learning techniques. Some of these literature closely related to the work reported are follows. Wenkai Huang et al had proposed a separable EEGNet (S-EEGNet) based on Hilbert_Huang transform (HHT) and a separable convolutional neural network (CNN) with bilinear interpolation [2]. They improved the accuracy of classification of the time and space dimensions of EEG. Meisel and Bailey developed deep learning networks that were trained on ECoG or EKG , to extract information from complex data [3]. They found that single-channel EKG contains a comparable amount of preictal information as scalp EEG with up to 21 channels and shown that preictal information is best extracted from the power spectral density. Al Ghayab et al proposed a tunable Q-factor wavelet transform (TQWT) based feature extraction method which has the potential to extract discriminative information from brain signals [4].

Ac et al. developed a passive EEG BCI for detecting a set of mental states, engaged or focused, disengaged or unfocused, and drowsing states [5]. Support Vector Machine (SVM) based classifier was reported for apnea detection using ECG signal by Almazaydeh et al. and shown that the machine learning based classifier can outperform the time domain and frequency domain analysis methods [6]. Damodar Reddy et al. developed a Random Forest (RF) classifier to identify the mental state as concentration and meditation using EEG signals [7]. Features are extracted from the pre-processed and band-limited EEG signals to classify apnea and normal cases using K-nearest neighbourhood (KNN) classifier in [8].

To enable efficient and faster classification, design and implementation of the classifier in suitable hardware is necessary. Hardware-based implementations rely on dedicated hardware designs that are used to speed up the classification process such as the ones implemented in Field Programmable Gate Array (FPGA). FPGA based design of different classifiers for specific applications were reported [9], [10].

In this paper, classifiers to detect SA from EEG data using the SVM and Random Forest (RF) machine learning algorithms are analysed. Based on the performance, RF is found to be more suitable for this application and hence the FPGA design of the same is also reported.

II. METHODOLOGY

Fig. 1 shows the methodology followed in the classification and analysis process. The raw recorded data from the data dataset is pre-processed to extract the sub-bands and present them as vectors for feature extraction. Then the samples are presented as a set of features to the classifier for testing. Prior to testing the training process is carried out with the features of the training set samples. Standard performance metrics are used to access the performance of the classifier.

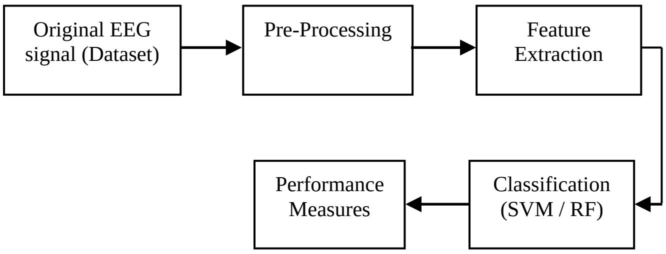

Fig. 1 Block diagram of the System Model

In SVM the sample data are considered to be points distributed in a 2-D plane and the effect of training is to identify the appropriate hyperplane separating the two classes [6]. RF algorithm employs a set of decision trees to solve the classification problem in a supervised learning manner. During the training process, each tree receives a random set of samples and while testing each test sample is applied to all the trees. The final decision is taken by means of voting the predictions of all the trees [7].

A. Dataset Used

Cyclic Alternating Pattern (CAP) is a periodic EEG activity that can serve as a marker of sleep instability and can be correlated with several sleep-related pathologies. A snippet of an EEG recording is shown in Fig. 2.

Fig. 2 Snippet of an EEG Recording of CAP

The annotated CAP sleep database from Physionet [11], which is a collection of EEG recordings from 108 people including 16 normal cases is used for training and testing. The sampling rate of 128 samples/sec and 12-bit ADC is used in acquiring the samples.

B. Feature Selection

The CAP data is pre-processed to extract the five sub-bands namely, alpha, beta, gamma, delta and theta. Sample frames of 20 seconds are derived from the 60 second recordings. Sample Entrophy (SE), Approximate Entropy (AE) and Recurrence Quantification Analysis Entrophy (RQE) are the features extracted from the samples for each sub-band. The number of feature variables is 15.

C. Performance Metrics

To access the performance of the classifier, standard statistical measures used are *Accuracy*, *Sensitivity* and *Specificity* which are defined as follows [8].

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$Sensitivity = TP / (TP + FN) \quad (2)$$

$$Specificity = TN / (TN + FP) \quad (3)$$

III. RESULTS AND DISCUSSION

For training the classifiers and testing the performance, 68 and 40 samples respectively are used. The confusion matrices of the SVM and RF classifiers are shown in Figs. 3 and 4 respectively.

Input/ Output	Normal	Apnea
Normal	**93.75%**	6.25%
Apnea	25%	**75%**

Fig.3 Confusion Matrix of SVM Apnea Classifier

Input/ Output	Normal	Apnea
Normal	**96.87%**	3.13%
Apnea	12.50%	**87.50%**

Fig.4 Confusion Matrix of RF Apnea Classifier

From the confusion matrices, it can be observed that the RF classifier is better suited than the SVM classifier for detection of sleep apnea. Table I shows the performance comparison of the two apnea classifiers in terms of the metrics specified by equations (1) to (3).

TABLE I
PERFORMANCE COMPARISON

Classifier	**Performance Metric**		
	Accuracy	**Sensitivity**	**Specificity**
SVM	92.18	87.50	96.87
RF	84.38	75.00	93.75

From the table, it can be observed that the RF based apnea classifier outperforms the SVM based apnea classifier by 9.25% in terms of accuracy.

As a step toward efficient real-time implementation of the classifier, RF based apnea classifier is designed to be implemented in FPGA. Figs. 5 to 7 shows the various building blocks of the RF classifier as synthesized schematics.

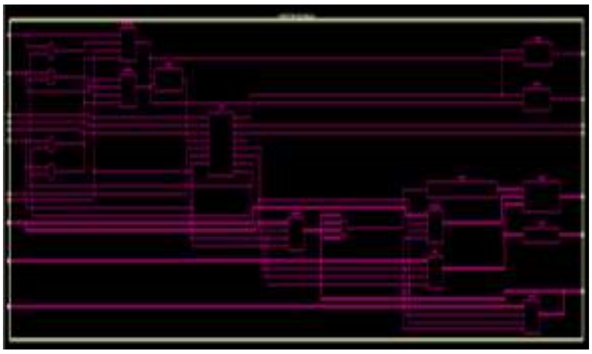

Fig.5 Schematic of the Internal Branch Stage

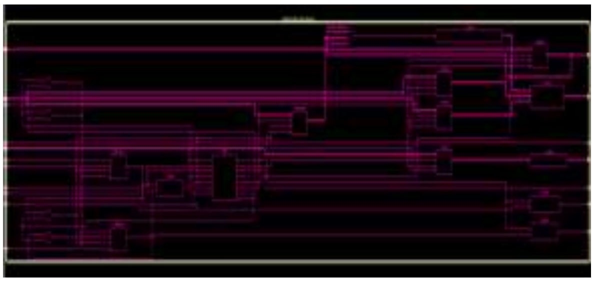

Fig.6 Schematic of the Internal Leaf Node

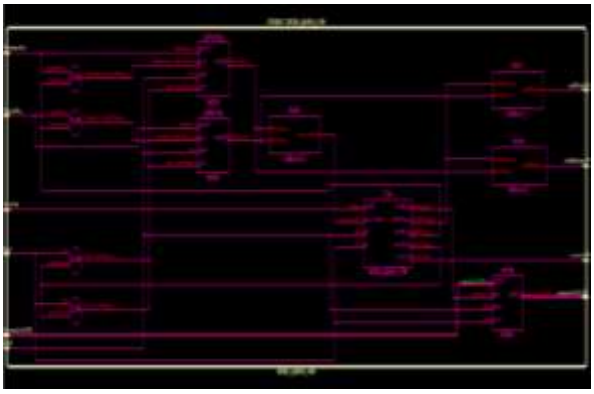

Fig.7 Schematic of the Pipeline Node

Verification of functionality of all the components of the RF apnea classifier has been done and the proposed system is synthesized using Cadence Software in System Verilog language.

IV. CONCLUSIONS

In this paper two widely used machine learning classifiers are analysed for sleep apnea classification application. An expert labelled CAP dataset of EEG recordings is used to train and test the classifiers. From the results obtained, it had been observed that the RF based classifier is better suited for the sleep disorder classification than SVM classifier. A 9.25% increase in classification accuracy is observed in the case of RF compared to that of SVM. FPGA design and functional verification is also carried out for the RF based apnea classifier. As a future extension of the work, other classifiers such as neural network and bio-inspired classifiers can also be applied for sleep apnea detection.

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